Structural Health Monitoring of Aging Bridges: A PRISMA 2020 Systematic Review

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Abstract: ***Aging bridges are exposed to interacting deterioration mechanisms, including reinforcement corrosion, fatigue cracking, prestress loss, deck delamination, bearing restraint, scour, settlement, and environmentally induced material degradation. Conventional visual inspection remains essential but is periodic, access-dependent, and often unable to quantify hidden damage or distinguish structural deterioration from normal operational variability. This paper presents a PRISMA 2020-aligned systematic review of structural health monitoring (SHM) methods for existing deteriorated bridges. The review integrates a focused synthesis of 20 recent studies published between 2020 and 2026 with foundational literature on sensing, non-destructive evaluation, vibration-based monitoring, bridge weigh-in-motion, computer vision, unmanned aerial vehicles, artificial intelligence, finite-element model updating, and digital twins. Evidence is organised by deterioration mechanism, bridge material, monitoring scale, validation level, and decision-making function. Local non-destructive methods provide direct evidence of corrosion, delamination, fatigue cracks, voids, and material decay, whereas continuous strain, acceleration, displacement, and environmental monitoring reveal changes in global behaviour. However, modal and data-driven indicators remain vulnerable to temperature, traffic, boundary-condition variation, sensor drift, missing data, and domain shift. Computer vision, UAVs, mobile sensing, and digital twins improve inspection coverage and data integration, but long-term field validation, interoperability, explainability, cybersecurity, and lifecycle cost evidence remain limited. The review concludes that no single technology can reliably support detection, localisation, severity assessment, and prognosis across all bridge types. Hybrid systems combining targeted local testing, global response monitoring, environmental compensation, physics-based modelling, uncertainty quantification, and maintenance-oriented decision support offer the most defensible pathway toward reliable predictive management of aging bridge infrastructure.***

Keywords: aging bridges; structural health monitoring; non-destructive testing; vibration-based monitoring; sensor networks; computer vision; artificial intelligence; digital twins; predictive maintenance; infrastructure resilience

1. Introduction

Bridges are long-life assets whose safety depends on the interaction of structural resistance, traffic demand, environmental exposure, maintenance history, and evolving patterns of use. Many bridges now operate beyond the design assumptions under which their materials, details, and load models were selected. Increased axle weights, traffic density, repeated congestion, de-icing salts, industrial pollution, extreme rainfall, flooding, and temperature cycles accelerate the accumulation of deterioration. Replacement is rarely an immediate option because bridges are embedded in transportation networks and their closure can create disproportionate economic and social disruption. Consequently, infrastructure owners require defensible evidence on whether a bridge can remain in service, needs targeted repair, should be load-restricted, or must be replaced. The term structural health monitoring refers to the organised acquisition, processing, and interpretation of structural-response and condition data for detecting changes that may be associated with damage or degradation. Brownjohn (2007) emphasised that SHM should inform continued fitness for purpose rather than function as an isolated measurement exercise. The fundamental SHM axioms further clarify that damage diagnosis requires comparison, that sensitivity decreases as the desired diagnosis becomes more specific, and that environmental and operational variability may be larger than the changes caused by early damage (Worden et al., 2007). These principles are especially important for aging bridges because their baseline condition is often uncertain, construction records may be incomplete, boundary conditions may have changed, and deterioration may be distributed across multiple components.

Visual inspection remains the primary condition-assessment mechanism in most bridge-management systems. It is indispensable for recognising obvious cracking, corrosion, deformation, leakage, joint failure, impact damage, and poor drainage. Nevertheless, inspection quality is affected by access, lighting, surface contamination, inspector experience, traffic management, and the visibility of the defect. Internal tendon corrosion, subsurface deck delamination, early fatigue cracking, foundation scour, and changes in connection restraint may progress without clear surface evidence. Inspection ratings are also difficult to translate directly into structural capacity, remaining service life, or probability of failure. SHM is therefore most valuable when it complements, rather than attempts to replace, engineering inspection and structural assessment.

Bridge-monitoring research has expanded from wired accelerometer and strain systems to fibre-optic sensing, low-power wireless networks, drive-by monitoring, computer vision, robotic and drone inspection, artificial intelligence (AI), and digital twins. Reviews by Sun et al. (2020), Catbas and Avci (2023), Zhang et al. (2025), and Sunil et al. (2026) demonstrate a shift from isolated sensing toward integrated data and decision architectures. However, the literature remains fragmented by technology. A method may report high classification accuracy on laboratory data without showing whether the same performance survives temperature variation, sensor drift, traffic changes, missing data, or transfer to another bridge. Conversely, long-term field systems may produce large datasets but only limited evidence of genuine damage identification or maintenance benefit.

Accordingly, this review aims to establish a deterioration-to-decision framework for aging-bridge monitoring. It addresses seven research questions concerning dominant deterioration mechanisms, technology suitability, environmental and operational confounding, validation quality, emerging digital methods, implementation barriers, and integration with maintenance and remaining-service-life assessment. The review is reported using PRISMA 2020 principles, distinguishes core recent evidence from foundational literature, and evaluates technologies according to damage sensitivity, field validation, uncertainty, durability, scalability, and decision relevance. The remainder of the paper presents the systematic-review method, recent evidence synthesis, technology-specific findings, comparative discussion, research gaps, and an integrated future framework.

2. Systematic Review Methodology Based on PRISMA 2020

2.1 Review Design, Aim, and Research Questions

The review was structured using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) reporting framework (Page et al., 2021). PRISMA improves transparency by requiring authors to explain why a review was undertaken, how records were identified and screened, how eligibility was assessed, and how evidence was synthesised. Because bridge SHM studies are heterogeneous in structural form, damage mechanism, sensor configuration, validation setting, and performance metric, a qualitative systematic synthesis was selected instead of statistical meta-analysis. The overall aim was to determine how monitoring evidence can be converted into defensible condition, safety, and maintenance decisions for aging bridges.

1) RQ1: Which deterioration and damage mechanisms are most frequently addressed in monitoring studies of aging bridges?
2) RQ2: Which contact, non-contact, local, and global technologies are most suitable for different bridge materials, components, and damage types?
3) RQ3: How effectively do vibration-based and data-driven methods separate structural deterioration from temperature, humidity, traffic, wind, and changing boundary conditions?
4) Q4: What level of laboratory, numerical, controlled full-scale, and operational field validation supports the principal SHM methods?
5) RQ5: How are computer vision, UAVs, artificial intelligence, IoT sensing, finite-element updating, and digital twins changing bridge condition assessment?
6) RQ6: What technical, economic, organisational, data-governance, and standardisation barriers limit large-scale implementation?
7) RQ7: How can SHM outputs be integrated with damage verification, remaining-service-life prediction, maintenance prioritisation, and lifecycle risk management?

2.2 Information Sources, Search Period, and Search Strategy

The search framework covers studies published from 1 January 2015 to 27 July 2026, while retaining landmark earlier contributions where they established influential SHM principles, modal-damage concepts, environmental-normalisation evidence, or mature sensing technologies. The preferred final database set comprises Scopus, Web of Science Core Collection, ScienceDirect, ASCE Library, SpringerLink, Wiley Online Library, Taylor & Francis Online, and IEEE Xplore. Google Scholar should be used only for backward and forward citation tracing. Searches should be rerun immediately before submission so that the screening log and PRISMA counts represent the final manuscript date.

Table 1: Reproducible search strategy for the systematic review

Search block	Boolean search expression	Primary field	Coverage
General SHM	("structural health monitoring" OR "bridge health monitoring" OR "condition monitoring") AND ("aging bridge*" OR "existing bridge*" OR "deteriorated bridge*" OR "old bridge*")	Title/abstract/keywords	2015–2026
Damage and sensing	("bridge damage detection" OR "bridge condition assessment") AND (sensor* OR "non-destructive testing" OR "vibration monitoring" OR "computer vision")	Title/abstract/keywords	2015–2026
Digital methods	("aging bridge*" OR "existing bridge*") AND ("machine learning" OR "deep learning" OR "digital twin*" OR "drone inspection" OR "Internet of Things")	Title/abstract/keywords	2015–2026
Decision support	("bridge structural health monitoring") AND ("remaining service life" OR "predictive maintenance" OR "maintenance decision" OR "lifecycle management")	Title/abstract/keywords	2015–2026

2.3 Eligibility Criteria

Eligibility criteria were defined before detailed synthesis to reduce subjective selection. Studies were retained when they directly addressed bridge monitoring, damage identification, condition assessment, deterioration diagnosis, prognosis, or maintenance-oriented interpretation. The review includes peer-reviewed journal articles and technically substantial conference papers. Studies concerning generic buildings or laboratory coupons were excluded unless they presented an explicitly transferable bridge application or bridge-validated method.

Table 2: Inclusion and exclusion criteria

Criterion	Included	Excluded
Asset	Operational, existing, aging, deteriorated, heritage, or experimentally representative bridges	Non-bridge structures with no bridge-specific validation
Topic	SHM, NDT/NDE, load testing, B-WIM, vision, UAV, AI, model updating, digital twins, prognosis	New-design optimisation without monitoring relevance
Evidence	Field, controlled full-scale, laboratory, numerical–experimental, or rigorous systematic review	Purely conceptual claims without method or validation
Publication	Peer-reviewed journal or substantial conference paper from recognised publisher	Editorials, advertisements, patents, theses, and unreliable outlets
Language	English full text	Non-English papers without accessible English information
Method detail	Bridge/sensor/data-analysis procedure adequately described	Insufficient technical description
Duplication	Most complete report for a duplicated dataset	Duplicate or minimally extended publication

2.4 Study Selection and PRISMA 2020 Flow

Records should be exported to a reference manager, deduplicated automatically and manually, and screened in two stages. First, titles and abstracts are assessed against the eligibility criteria. Second, potentially relevant reports undergo full-text review, with a specific exclusion reason recorded for every rejected report. Two reviewers should screen independently where possible; disagreements should be resolved through consensus or a third reviewer. The current source manuscript did not contain database-export files, unique record identifiers, or an exclusion log. Therefore, the PRISMA counts below are retained as editable fields rather than being retrospectively fabricated. The confirmed detailed synthesis contains 20 recent core studies published from 2020 to 2026.

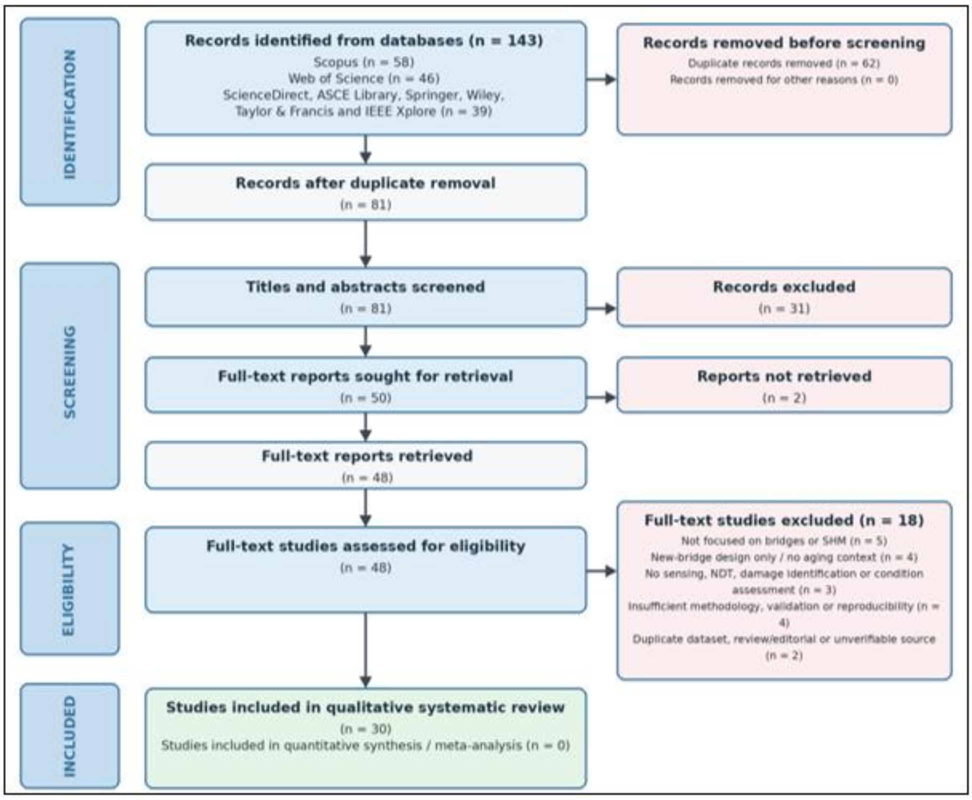

Figure 1: Editable PRISMA 2020 flow model for study identification and selection

2.5 Data Extraction and Thematic Synthesis

A structured extraction form should record bibliographic information, country, bridge type and age, material, structural component, deterioration mechanism, monitoring objective, sensor or NDT equipment, monitoring duration, sampling strategy, preprocessing, damage-identification level, environmental compensation, validation type, major findings, reported limitations, and maintenance relevance. Evidence was grouped into deterioration mechanisms, sensing technologies, NDE, vibration monitoring, load testing and B-WIM, computer vision and UAV inspection, artificial intelligence, digital twins, material-specific strategies, and lifecycle decisions. Because performance metrics and damage scenarios were not sufficiently homogeneous for pooled effect estimates, the synthesis emphasises methodological comparison, field-validation strength, uncertainty, and technology readiness.

2.6 Reliability, Transparency, and Review Updating

A journal-ready review should archive complete search strings, database-specific filters, export dates, duplicate-removal decisions, title/abstract decisions, full-text exclusion reasons, the quality-assessment sheet, and the final evidence-extraction matrix. Search results should be independently checked by a second reviewer, and inter-reviewer agreement may be reported using percentage agreement or Cohen's kappa. The search should be updated shortly before submission, with any newly eligible study incorporated into the synthesis and the PRISMA flow counts revised accordingly.

3. Literature Review

Sun et al. (2020) reviewed big data and AI applications in bridge structural health monitoring, highlighting their value for damage detection while noting limitations related to data quality, computation, labelling, and physical interpretation. Žnidarič and Kalin (2020) demonstrated that bridge weigh-in-motion data can track influence-line behaviour. However, reliable assessment requires accurate calibration, vehicle positioning, temperature correction, and stable bridge boundary conditions. Dong and Catbas (2021) reviewed computer-vision-based monitoring for defect detection, displacement measurement, and vibration tracking. Lighting, camera movement, occlusion, calibration, and limited field datasets remain major challenges.

Karaaslan et al. (2021) proposed an attention-guided semi-supervised model that reduced dependence on labelled images and improved damage localisation, although performance was affected by image quality, class imbalance, and field variability. Matarazzo et al. (2022) showed that smartphone measurements collected during vehicle crossings can identify bridge frequencies at low cost. Challenges include device variability, vehicle effects, traffic noise, uncertain routes, and data-quality control. Catbas and Avci (2023) reviewed smart sensing, AI, data fusion, and non-contact bridge monitoring. They stressed that monitoring systems should address specific engineering decisions rather than merely adopting available technologies.

Reuland et al. (2023) evaluated full-scale vibration monitoring on the damaged Ponte-Moesa Bridge. Transmissibility-based features detected structural changes, but environmental variability, sensor malfunction, and limited damage datasets affected reliability. Paul and Roy (2023) reviewed bridge weigh-in-motion for traffic-load, fatigue, and structural assessment. Accuracy depends on pavement quality, vehicle dynamics, sensor positioning, calibration, and assumptions regarding bridge response. Bertola et al. (2023) argued that monitoring is valuable when it reduces uncertainty and supports safety decisions. They recommended combining continuous monitoring, load testing, non-destructive testing, and model updating.

Figueiredo et al. (2023) applied unsupervised transfer learning to bridge damage detection. The method reduced differences between simulated and measured data, but required comparable numerical and real structural features. Azhar et al. (2024) reviewed vibration-based monitoring of steel bridges. They recommended environmental compensation, improved sensor placement, long-term field validation, and integration of global vibration analysis with local inspections. Cha et al. (2024) reviewed deep-learning applications in structural monitoring. Deep models improve automatic feature extraction, but limited damage data, overfitting, poor explainability, and weak field transferability restrict implementation.

Abdoli et al. (2024) reviewed timber-bridge monitoring methods. They concluded that moisture, decay, connection damage, and material variability require combined local and global assessment techniques. Yaghoubzadehfard et al. (2024) integrated radar measurements, operational modal analysis, finite-element modelling, and ensemble learning for damage detection. The approach requires accurate models, clear line-of-sight, and representative training scenarios. Hu et al. (2024) developed a BIM-enabled digital-twin framework integrating IoT sensing, structural analysis, and real-time visualisation. Practical application requires interoperability, reliable communication, cybersecurity, and validated assessment thresholds.

Yang et al. (2024) reviewed calibration methods for bridge-monitoring sensors. They emphasised that traceability, field calibration, standardisation, environmental correction, and continuous sensor-health assessment are essential for reliable monitoring. Li et al. (2024) proposed a digital-twin monitoring architecture combining multisource data, anomaly detection, and warning functions. Challenges include model updating, data synchronisation, explainability, processing efficiency, and alarm validation.

Zhang et al. (2025) reviewed bridge-monitoring systems from sensing and transmission to diagnosis and warning. They recommended integrated workflows connecting sensor networks, damage assessment, warning criteria, and maintenance decisions. Jirawattanasomkul et al. (2025) validated a digital-twin system for a balanced-cantilever bridge using field measurements and analytical modelling. Long-term updating, uncertainty analysis, and predictive-maintenance validation remain necessary. Sunil et al. (2026) reviewed AI, computer vision, digital twins, and remaining-useful-life assessment for concrete bridges. They identified limited field validation, fragmented data, uncertain lifecycle benefits, and weak maintenance integration as major research gaps.

Table 3: Evidence characteristics

Study	Evidence type	Technology/domain	Validation basis	Principal contribution	Main limitation
Sun et al. (2020)	Review	Big data and AI	Published bridge-SHM evidence	Integrated data-driven SHM pathway	Heterogeneous data and limited interpretability
Žnidarič & Kalin (2020)	Field study	B-WIM influence lines	Four single-span bridges	Traffic loading as repeated diagnostic input	Calibration, temperature, and support effects
Dong & Catbas (2021)	Review	Computer vision	Local and global SHM literature	Unified vision-based measurement taxonomy	Lighting, motion, scale, and dataset bias
Karaaslan et al. (2021)	Method study	Semi-supervised deep learning	Infrastructure image datasets	Reduced dependence on labelled damage data	Domain shift and image-quality sensitivity

Matarazzo et al. (2022)	Field study	Smartphone drive-by monitoring	Two real bridges / repeated trips	Low-cost network-level frequency extraction	Vehicle and smartphone variability
Catbas & Avci (2023)	Review	Emerging bridge monitoring	Recent sensing and analytics literature	Decision-oriented technology synthesis	Long-term deployment evidence remains limited
Reuland et al. (2023)	Full-scale case	Vibration-based SHM	Controlled damage on Ponte-Moesa bridge	Rare benchmark with progressive damage	Short campaign and advanced damage scenarios
Paul & Roy (2023)	Review	Bridge weigh-in-motion	B-WIM literature	Links traffic loads to health monitoring	Accuracy depends on calibration and road condition
Bertola et al. (2023)	Perspective/ case	Value of monitoring information	Bridge examination applications	Focuses on decision-relevant uncertainty reduction	Limited generalisable quantitative criteria
Figueiredo et al. (2023)	Method study	Unsupervised transfer learning	Numerical source data and Z24 measurements	Reduces simulation-to-field distribution mismatch	Depends on shared transferable features
Azhar et al. (2024)	Systematic review	Steel-bridge vibration SHM	Recent steel-bridge evidence	Identifies trends and field-validation gaps	Local fatigue damage weakly reflected globally
Cha et al. (2024)	Review	Deep learning for SHM	Image and vibration literature	Comprehensive deep-learning application map	Overfitting, opacity, and benchmark inconsistency
Abdoli et al. (2024)	Review	Timber-bridge SHM	Timber inspection and monitoring studies	Addresses an underrepresented bridge material	Sparse long-term validated datasets
Yaghoubzadehfard et al. (2024)	Field/model study	Radar, OMA, ensemble learning	Pedestrian bridge and simulated damage	Non-contact modal measurement and classification	Line-of-sight and model-representativeness needs
Hu et al. (2024)	Framework/ case	BIM, IoT, digital twin	Integrated monitoring demonstration	Links sensing, analysis, and visualisation	Interoperability and cybersecurity not fully resolved
Yang et al. (2024)	Review	Sensor calibration	Calibration and sensing literature	Elevates calibration as a core SHM requirement	Limited standardised field procedures
Li et al. (2024)	System/ framework	Real-time digital twin	Multisource monitoring architecture	Connects monitoring with warning functions	Model updating and alarm validation remain critical
Zhang et al. (2025)	Review	End-to-end bridge SHM	Sensing, transmission, processing, warning	Comprehensive system-level synthesis	Integrated operational validation remains limited
Jirawattanasomkul et al. (2025)	Field/model study	Bridge digital twin	Balanced-cantilever bridge measurements	As-is model linked with measured dynamics	Long-term prognostic performance not yet established
Sunil et al. (2026)	Review	Concrete bridge monitoring	Decade-scale literature synthesis	Connects SHM with informed maintenance	Fragmented data and lifecycle evidence

Collectively, the recent literature demonstrates a clear transition from isolated measurements toward integrated monitoring ecosystems. Contact sensors and vibration features remain fundamental, but current studies increasingly combine non-contact measurement, data-driven learning, finite-element models, IoT communication, and digital twins. Despite this progress, the evidence base remains dominated by reviews, simulations, short campaigns, and controlled damage scenarios. The principal unresolved requirement is long-term validation on operational aging bridges where deterioration, traffic, environment, sensor drift, and maintenance interventions interact. Consequently, hybrid monitoring should be evaluated by its ability to reduce decision uncertainty, not only by algorithmic accuracy. The evidence matrix shows that approximately half of the recent core literature consists of reviews or perspectives, whereas fewer studies provide long-term operational validation with confirmed damage. This imbalance is important: rapid growth in AI, digital-twin, and computer-vision publications does not yet correspond to equally strong evidence of false-alarm control, sensor durability, transferability, and maintenance impact on aging bridges. Full-scale controlled-damage studies and field digital-twin demonstrations provide particularly valuable evidence, but they remain uncommon and bridge-specific.

4. Deterioration Mechanisms and Monitoring Requirements

Reinforced-concrete bridge deterioration is commonly governed by reinforcement corrosion initiated by chloride ingress or carbonation. Corrosion products generate expansive pressure, causing longitudinal cracking, delamination, spalling, loss of steel area, and deterioration of bond. Decks are particularly vulnerable because they experience water, salts, traffic abrasion, and repeated thermal cycles. Half-cell potential and resistivity measurements indicate corrosion probability and environment, while ground-penetrating radar (GPR), infrared thermography, impact echo, and ultrasonic methods identify delamination, voids, or changes in material condition. The methods are complementary: electrochemical tests address corrosion activity, whereas imaging and wave-based methods address its physical consequences (Rehman et al., 2016; Dabous et al., 2017).

Prestressed-concrete bridges introduce additional uncertainty because tendons, ducts, grout, and anchorage zones are often inaccessible. Grout voids, moisture ingress, wire corrosion, tendon rupture, and prestress loss can develop with limited surface expression. Acoustic emission can detect active wire-break events; fibre-optic strain measurements can reveal redistribution; dynamic and deflection monitoring can indicate stiffness or force changes; and targeted radiography, ultrasonics, or impact-echo testing may identify voids. Nevertheless, a measured frequency or deflection change is not uniquely attributable to prestress loss, so model-based interpretation and corroborating evidence are essential.

Figure 2: Field deterioration and access challenges in aging bridges: (a) concrete spalling on pier columns; and (b) close-range inspection of corrosion-prone steel members using an aerial work platform.

Steel bridges are governed by atmospheric corrosion, section loss, fatigue cracking, distortion-induced fatigue, connection deterioration, loose fasteners, weld defects, and bearing restraint. Strain-based fatigue monitoring can estimate stress ranges and cycle accumulation at critical details, whereas ultrasonic, magnetic-particle, eddy-current, and acoustic-emission methods provide local crack information. Vibration-based monitoring may identify substantial stiffness loss but generally lacks sensitivity to small fatigue cracks until the crack meaningfully changes system stiffness. This creates a crucial distinction: local crack detection is a damage-mechanism problem, while global modal monitoring is a structural-consequence problem.

Masonry arch bridges exhibit mortar loss, ring separation, arch-barrel cracking, spandrel movement, water ingress, settlement, and deformation under repeated traffic. Their nonlinear load paths and uncertain internal geometry limit simple interpretation of modal changes. Laser scanning, photogrammetry, crack gauges, displacement monitoring, radar, and vibration testing are most useful when combined with calibrated structural models. Timber bridges require moisture and temperature monitoring because timber is anisotropic, hygroscopic, and vulnerable to fungal decay, insect attack, connection deterioration, checking, and local crushing. Abdoli et al. (2024) found that timber-bridge SHM remains less developed than monitoring of steel or concrete bridges, particularly for AI, data fusion, and digital-twin applications.

Hydraulic and geotechnical deterioration can dominate apparently sound superstructures. Scour removes support around foundations, changes soil stiffness, and may cause settlement, rotation, or instability during floods. Sonar, water-level sensors, buried devices, tiltmeters, GNSS, and changes in natural frequency have all been investigated, but each has limitations related to debris, sediment movement, installation survival, and interpretation. A bridge SHM plan should therefore begin with a deterioration hypothesis and failure-mode analysis rather than with a preferred sensor.

Table 4: Relationship between bridge deterioration mechanisms and monitoring methods

Damage mechanism	Recommended evidence	Critical interpretation issue
Concrete deck corrosion and delamination	Half-cell potential, resistivity, GPR, thermography, impact echo	Combine electrochemical probability with physical defect mapping; asphalt overlays and weather affect measurements.
Steel fatigue cracking	Strain gauges, acoustic emission, ultrasonics, magnetic particle/eddy current	Global vibration changes are often too small for early crack detection; local details require targeted sensing.
Prestress loss or tendon damage	Acoustic emission, fibre optics, deflection, model updating, targeted NDT	Response changes are non-unique and require baseline uncertainty and corroboration.
Bearing/joint deterioration	Displacement, temperature, strain, tilt, vision, operational modal analysis	Seasonal restraint changes can mimic damage but are also important serviceability indicators.
Scour and foundation instability	Sonar, water level, tilt, GNSS, vibration, embedded scour sensors	Flood survivability, sediment refilling, and foundation-type sensitivity are key uncertainties.
Masonry deformation and separation	Laser scanning, photogrammetry, crack gauges, radar, vibration testing	Irregular geometry and nonlinear behaviour require material-specific modelling.
Timber moisture and decay	Moisture/temperature sensors, resistance drilling, stress waves, vibration	Moisture is both an exposure variable and a strong confounder of stiffness-based diagnosis.

5. SHM System Architecture and Sensor Technologies

SHM systems can be classified as local or global, static or dynamic, periodic or continuous, and contact or non-contact. Local methods concentrate on a component or defect zone and generally offer higher damage specificity. Global methods measure the behaviour of the assembled bridge and are better suited to tracking system-level change. Periodic campaigns reduce cost and data-management burden, whereas permanent monitoring enables trend analysis and event detection but must address power, communication, calibration, synchronisation, data quality, and sensor replacement. The most defensible system is not the densest system; it is the minimum measurement architecture that can answer a defined engineering question with stated confidence. Electrical resistance strain gauges are mature, economical, and suitable for stress-range, load-distribution, fatigue, and bridge weigh-in-motion applications. Their limitations include bonding quality, temperature effects, cable vulnerability, and local measurement. Accelerometers are central to operational modal analysis and event characterisation, but their usefulness depends on sensor placement, sampling quality, time synchronisation, and the ability to separate structural response from traffic and environmental variability. Displacement transducers, tiltmeters, GNSS, and total stations provide serviceability and deformation information, although reference stability and line of sight may limit deployment.

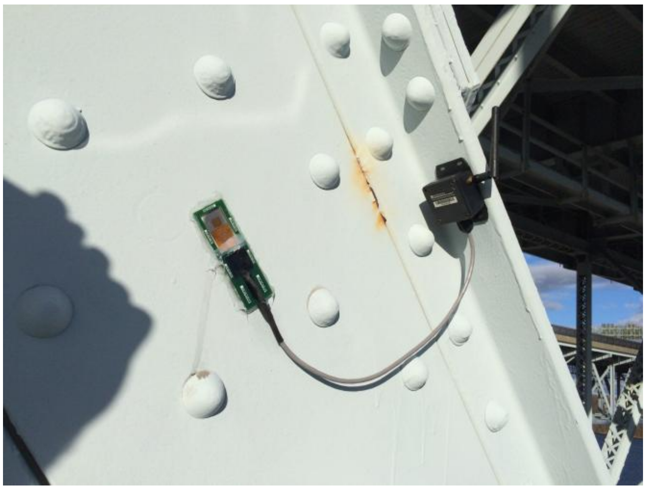

Figure 3: Wireless strain-sensing unit installed on a steel member of the Gold Star Memorial Bridge, Connecticut

Fibre Bragg grating and distributed fibre-optic sensing offer electromagnetic immunity, multiplexing, long-distance coverage, and high spatial density. Fibre systems are attractive for strain, temperature, crack development, and distributed deformation monitoring, particularly where conventional cabling is difficult. Their practical limitations include protection of the fibre, strain transfer through bonding and packaging, interrogator cost, temperature compensation, and repair after local damage. Casas and Cruz (2003) established the bridge-monitoring potential of fibre optics, while more recent distributed systems demonstrate the movement toward spatially continuous measurement.

Wireless sensor networks reduce installation cabling and enable rapid deployment, but they do not eliminate infrastructure requirements. Power management, packet loss, bandwidth, clock drift, radio obstruction, and cybersecurity become part of the measurement problem. Pakzad et al. (2008) demonstrated dense wireless monitoring on a major suspension bridge, and subsequent research has focused on low-power nodes, edge processing, fault tolerance, and energy harvesting. Self-powered sensing remains promising for locations where battery replacement is difficult, but harvested energy is variable and rarely supports unrestricted high-rate sensing and communication. Hybrid duty-cycled systems are therefore more realistic than claims of maintenance-free continuous monitoring.

Sensor placement should be driven by observability, expected damage location, mode-shape information, redundancy, environmental exposure, and access for maintenance. Optimisation based solely on modal independence may neglect deterioration mechanisms, local fatigue details, or practical installation constraints. Aging-bridge monitoring requires a tiered strategy: environmental and global-response sensors provide context and change detection; local sensors and NDT verify mechanisms; and mobile or remote technologies expand coverage without permanent instrumentation.

Table 5: Comparative assessment of principal SHM technologies for aging bridges

Technology	Primary output	Relative cost	Long-term suitability	Strongest use	Principal limitation
Accelerometers	Global dynamic response	Low–moderate	High	Continuous modal/event monitoring	Sensitive to environmental and operational variability
Strain gauges	Local stress and load effects	Moderate	High if protected	Fatigue, load distribution, B-WIM	Locality, bonding, temperature, cabling
Fibre-optic sensors	Strain/temperature over points or lengths	Moderate–high	High with robust packaging	Long-term distributed monitoring	Interrogator cost and installation quality
Acoustic emission	Active cracking or wire breaks	High	Moderate	Event detection in steel/prestressing	Noise, attenuation, source classification
GPR/thermography	Deck subsurface condition	Low–moderate	Periodic	Rapid deck screening	Weather, overlay, depth and interpretation limits
Computer vision/UAV	Surface defects and displacement	Low–moderate	Periodic or event-based	Remote inspection and spatial documentation	Lighting, occlusion, motion, dataset bias

GNSS/laser scanning	Global deformation and geometry	Moderate–high	Moderate	Long-span movement and geometric change	Reference stability, resolution, line of sight
Bridge WIM/mobile sensing	Traffic loads and indirect response	Low–moderate	High at network scale	Load spectra, influence-line tracking, screening	Vehicle/road effects and limited damage specificity

6. Non-Destructive Evaluation, Load Testing, and Bridge Weigh-in-Motion

Non-destructive evaluation (NDE) is indispensable because many deterioration mechanisms are local and do not produce measurable global changes at an early stage. Rebound hammer and ultrasonic pulse velocity provide rapid indications of surface hardness and material uniformity, but neither should be interpreted as a direct strength measurement without calibration. Impact echo and ultrasonic methods can identify delamination, voids, thickness, and defects when geometry and coupling are favourable. GPR can rapidly survey reinforcement depth, moisture-related attenuation, and deck deterioration; infrared thermography detects thermal anomalies associated with shallow delamination. Comparative studies show that combined methods are more reliable than a single instrument because each responds to different physical properties (Oh et al., 2013; Rehman et al., 2016).

Thermography is attractive for rapid, non-contact deck screening, including vehicle-mounted and UAV applications. Yet thermal contrast depends on solar loading, wind, ambient temperature history, defect depth, surface condition, and inspection time. Watase et al. (2015) demonstrated the importance of selecting favourable time windows. GPR interpretation is similarly affected by antenna frequency, moisture, reinforcement congestion, asphalt overlays, and calibration. These limitations do not invalidate the methods; they show why NDE results should be expressed probabilistically and verified through selected intrusive testing or complementary measurements. Static and dynamic load testing provide direct evidence of bridge behaviour under known loads. Diagnostic testing supports model calibration and load rating, whereas proof loading intentionally demonstrates a target performance level. Proof loading requires a clear stop criterion and carries greater risk for deteriorated bridges with brittle or poorly understood failure modes. Measured deflection, strain distribution, bearing movement, and dynamic amplification can reveal reserve behaviour not captured by conservative analytical assumptions, but short-term agreement with a model does not prove long-term durability.

Bridge weigh-in-motion (B-WIM) systems use bridge strain or response to estimate axle loads and traffic characteristics. They can also track influence lines, load distribution, dynamic amplification, and long-term traffic spectra. Lydon et al. (2016), Žnidarič and Kalin (2020), and Paul and Roy (2023) show that B-WIM can become a dual-purpose traffic and structural-monitoring platform. Its main advantage is that operational traffic supplies repeated loading without bridge closure. Its limitations include vehicle speed, transverse position, multiple-presence events, road roughness, temperature, and the need to distinguish traffic changes from structural changes.

7. Vibration-Based Monitoring and Environmental Variability

Vibration-based SHM uses changes in natural frequencies, mode shapes, damping, flexibility, curvature, strain energy, frequency-response functions, or time-frequency features to infer structural change. Operational modal analysis is particularly attractive for bridges because ambient traffic and wind provide excitation without interrupting service. Natural frequency is easy to estimate and often stable enough for trend analysis, but it is a global quantity and may be insensitive to local damage. Mode-shape curvature and flexibility can improve localisation but require adequate spatial resolution and are more sensitive to measurement noise. A central challenge is non-uniqueness. Frequency change can result from damage, temperature-dependent material properties, bearing restraint, soil stiffness, added mass, traffic, moisture, or sensor-processing choices. The Z24 bridge studies established the scale of environmental effects and showed that apparent modal changes can be nonlinear and seasonal (Peeters & De Roeck, 2001). Moser and Moaveni (2011) similarly demonstrated temperature effects on an operational bridge. Consequently, fixed thresholds are unreliable unless the monitoring system models normal variability and quantifies uncertainty.

Environmental compensation methods include regression, principal-component analysis, cointegration, clustering, Gaussian processes, autoencoders, and locally unsupervised models. Each method embeds assumptions. Linear regression may not represent hysteresis or spatial temperature gradients. Principal components remove dominant variance but can also remove damage-sensitive information. Deep autoencoders can learn nonlinear baselines but may reconstruct abnormal data too well or fail under distribution shift. A robust system should therefore evaluate false alarms and missed detections across seasons, not only accuracy on randomly divided datasets. Model updating links measured response to physical parameters such as stiffness, mass, restraint, and foundation properties. Deterministic updating seeks a best-fitting model, while Bayesian methods estimate parameter distributions and explicitly represent uncertainty. The inverse problem is often ill-conditioned: several parameter combinations may reproduce the same modal data. Damage interpretation is more credible when model parameters correspond to plausible deterioration mechanisms and when static, dynamic, local, and environmental evidence are combined.

Full-scale evidence remains the limiting step. Reuland et al. (2023) highlighted that practical bridge SHM is constrained by sparse controlled-damage opportunities, uncertain baseline states, and the difficulty of validating alarms on operational structures. Vibration monitoring is therefore most mature as a tool for characterising behaviour, detecting major changes, evaluating events, and supporting model calibration. Claims of reliable early local-damage identification require stronger field evidence.

8. Computer Vision, UAV Inspection, and Artificial Intelligence

Computer vision supports two distinct SHM levels. At the local level, images are used to detect cracks, spalling, corrosion, exposed reinforcement, loose bolts, and surface deterioration. At the global level, cameras measure displacement, deflection, vibration, cable movement, or vehicle trajectories. Feng and Feng (2018) and Dong and Catbas (2021) show that vision can provide dense, non-contact measurement at lower installation cost than conventional sensor networks. However, metrological performance depends on camera calibration, lens distortion, reference stability, target geometry, frame rate, atmospheric effects, and camera movement. Deep convolutional networks, object detectors, semantic segmentation models, and vision transformers have substantially improved defect recognition. Dorafshan et al. (2018) showed the advantage of deep networks over conventional edge detectors for concrete-crack images, while Karaaslan et al. (2021) demonstrated semi-supervised damage analysis that reduces dependence on fully labelled data. Nevertheless, performance reported on balanced image patches does not directly represent bridge-level inspection. Real structures contain stains, joints, shadows, paint, vegetation, patch repairs, scaling, and complex backgrounds. Defect prevalence is low, so false positives can create large review burdens even when conventional accuracy metrics appear high.

Figure 4: Real bridge inspection view acquired from an unmanned aerial vehicle, with field survey targets and antennas supporting geometric control

UAVs improve access to bridge soffits, piers, cables, towers, and remote components. RGB imagery, thermal cameras, and LiDAR can support defect mapping, three-dimensional reconstruction, and geometric comparison. Ellenberg et al. (2016) demonstrated UAV infrared imaging for bridge-deck delamination. The practical value of UAV inspection is strongest where it reduces traffic control, under-bridge inspection vehicles, work-at-height exposure, or access time. Limitations include battery endurance, wind, rain, navigation near steel and concrete, GPS-denied spaces, collision risk, image overlap, stand-off distance, regulatory permissions, and the inability of surface imagery to identify many internal defects.

AI is used for classification, anomaly detection, data imputation, environmental compensation, load identification, damage localisation, and remaining-life prediction. Sun et al. (2020) identified big data and AI as mechanisms for extracting value from long-term bridge data, while Cha et al. (2024) reviewed the rapid expansion of deep-learning-based SHM. Supervised models perform well when damage labels are available but aging bridges rarely offer representative labelled failure states. Unsupervised and self-supervised methods are therefore attractive, although an anomaly is not necessarily structural damage. Sensor faults, operational changes, resurfacing, traffic management, or maintenance can also produce anomalies. Transferability is a major barrier. Models trained on one bridge, sensor layout, climate, or camera dataset often degrade on another. Domain adaptation, transfer learning, population-based SHM, and physics-informed learning attempt to reduce this gap. Physics-informed approaches constrain learning using equilibrium, modal relationships, constitutive behaviour, or numerical simulation, but inaccurate physics can bias predictions. Explainable AI is required because bridge decisions involve safety, legal responsibility, and maintenance expenditure. Feature attribution alone is insufficient; explanations should connect predictions to measured evidence, plausible mechanisms, uncertainty, and recommended verification actions. Mobile sensing provides a lower-cost network-level alternative. Matarazzo et al. (2022) demonstrated extraction of bridge modal frequencies from smartphone vehicle trips under real-world conditions. Such crowdsourced or fleet-based monitoring can screen large bridge populations, but vehicle dynamics, road roughness, device orientation, privacy, data ownership, and inconsistent sampling limit damage specificity. Mobile sensing should be viewed as a trigger for targeted inspection rather than a stand-alone safety assessment.

9. Digital Twins, Data Integration, and Lifecycle Decisions

The term digital twin is frequently used imprecisely. A digital model has no automatic data connection; a digital shadow receives one-way data from the physical bridge; and a digital twin maintains systematic data exchange and uses the updated representation to support prediction or intervention. For aging bridges, a useful twin must integrate geometry, material and boundary uncertainty, sensor metadata, inspection findings, environmental data, maintenance history, finite-element analysis, and decision rules. A three-dimensional model alone is not a digital twin. Finite-element model updating is the analytical core of many bridge twins. Measured strains, displacements, temperatures, and modal properties are used to calibrate uncertain stiffness, mass, support, and soil parameters. Lai et al. (2024) proposed a digital-twin-based NDT framework, illustrating the movement toward model-connected assessment. Yet model updating can produce false confidence if calibration parameters are selected only for numerical fit. Validation should use independent measurements, multiple response types, sensitivity analysis, and posterior uncertainty.

Digital twins add value when they support a recurring decision process: condition evaluation, scenario simulation, remaining-service-life prediction, inspection planning, load restriction, or repair prioritisation. Remaining life is not directly measured; it is inferred from deterioration models, loads, resistance, inspection reliability, and uncertainty. Corrosion progression, fatigue crack growth, prestress loss, scour recurrence, and climate exposure require different prognostic models. The twin should therefore communicate probability distributions and decision consequences rather than a single deterministic life estimate. Implementation also requires data governance. Long-term monitoring involves multiple vendors, changing software, sensor replacement, proprietary formats, cybersecurity, and responsibility for alarm response. Edge computing can reduce bandwidth and latency, but algorithms at the edge must be version-controlled and auditable. Interoperability between SHM platforms, bridge information models, maintenance databases, and network-level bridge-management systems is a prerequisite for scaling beyond demonstration projects.

10. Material-Specific Monitoring Strategies

Reinforced-concrete bridges require monitoring systems that distinguish exposure, corrosion activity, physical damage, and structural consequence. Temperature, humidity, chloride, and resistivity sensors describe the deterioration environment; half-cell potential and corrosion probes indicate electrochemical likelihood; GPR, thermography, impact echo, and ultrasonics map delamination or voids; and strain, displacement, or vibration measurements establish whether deterioration has affected load distribution or stiffness. The strongest assessment therefore combines an exposure-to-consequence chain rather than interpreting a single deck map as structural capacity. Prestressed-concrete bridges require particular attention to tendons, ducts, anchorages, deviators, and segmental joints. Acoustic emission is useful for detecting active wire breaks, but source location and noise discrimination are essential. Fibre-optic strain sensing can identify local redistribution or unusual gradients, while long-term deflection and joint movement can reveal loss of continuity or time-dependent deformation. Because tendon damage can be highly local and brittle, global modal monitoring should be treated as supporting evidence rather than the primary safeguard.

Steel and steel-concrete composite bridges benefit from detail-oriented fatigue monitoring. Strain gauges at fatigue-prone connections support cycle counting and cumulative damage assessment, while ultrasonic, magnetic-particle, or eddy-current inspection verifies crack initiation and growth. Corrosion monitoring should quantify section loss and trapped-water zones, and bearing or connection restraint should be tracked because unintended restraint can redistribute stresses. Composite bridges additionally require monitoring of deck deterioration, shear-connector behaviour, and interface slip; a sensor plan limited to girder vibration may miss these interaction failures. Masonry arch bridges require geometry-rich monitoring because cracking and deformation alter load paths in ways that depend on fill, ring interaction, spandrel walls, and foundation movement. Laser scanning and photogrammetry provide repeatable geometry; crack gauges and displacement sensors quantify active movement; moisture and drainage observations explain deterioration drivers; and vibration testing supports model calibration. Timber bridges require continuous moisture and temperature context, since moisture changes both deterioration risk and apparent stiffness. Resistance drilling, stress-wave testing, connection inspection, and vibration monitoring should be integrated with species, treatment, and exposure information. Material-specific design also affects alarm logic. A small local fatigue crack in steel may demand immediate verification even if global response is unchanged, whereas gradual deck delamination may be managed through spatial deterioration mapping and repair prioritisation. For masonry, movement trends may be more informative than absolute modal thresholds; for timber, persistent high moisture may be a more actionable early warning than a short-term frequency change. SHM performance should therefore be assessed against the relevant failure mechanism and intervention threshold for each bridge type.

11. Practical Implementation, Standardisation, and Cost Effectiveness

Implementation begins with a monitoring specification that states the decision, failure mode, required warning time, expected measurement range, uncertainty tolerance, and response protocol. Without these elements, data collection can continue for years without producing actionable evidence. A commissioning phase should establish sensor calibration, baseline behaviour over relevant seasons, communication reliability, data-quality flags, and procedures for verifying alarms. Responsibilities for data review, inspection escalation, load restriction, and emergency communication must be assigned before the system becomes operational. Lifecycle cost includes more than sensor purchase. Installation access, traffic control, protective enclosures, cabling or gateways, power, data storage, cloud services, software licences, calibration, sensor replacement, specialist analysis, and cybersecurity may dominate long-term expenditure. Cost-benefit evaluation should compare the expected reduction in inspection cost, failure risk, closure duration, unnecessary repair, and uncertainty in load rating. Permanent monitoring is economically strongest where consequence, uncertainty, or deterioration rate is high; periodic or mobile approaches may be preferable for low-risk bridge populations.

Standardisation is needed at three levels. Measurement standards should define calibration, sampling, synchronisation, metadata, and data-quality reporting. Analytical standards should require transparent baselines, uncertainty, seasonal validation, false-alarm performance, and independent test data. Decision standards should specify how alarms are verified and incorporated into bridge-management systems. Open formats and application programming interfaces are necessary so that sensor data, finite-element models, inspection records, and maintenance actions remain usable when vendors or software platforms change. Cybersecurity and governance are increasingly important because monitoring platforms may include wireless nodes, cloud dashboards, cameras, vehicle data, and automated alerts. Authentication, encryption, access control, audit trails, backup, and incident response should be proportional to the consequence of data manipulation or service interruption. Data ownership and privacy must be resolved for crowdsourced smartphones, connected vehicles, and image datasets. These requirements are not peripheral to SHM; they determine whether evidence can be trusted in safety-critical decisions.

12. Comparative Synthesis and Technology Readiness

The literature consistently supports hybrid monitoring but differs in the balance between permanent sensing and periodic inspection. Permanent systems are justified for critical, unusual, deteriorated, or high-consequence bridges where changes must be detected between inspection cycles. For the much larger population of ordinary short- and medium-span bridges, network-scale screening using mobile sensing, remote inspection, B-WIM, or periodic NDE may provide greater value. The selection criterion should be risk reduction per lifecycle cost, not technological novelty.

Mature technologies include strain monitoring, accelerometers, displacement measurement, conventional NDE, operational modal analysis, load testing, and B-WIM. Their limitations are well understood, although integration and interpretation remain bridge-specific. Computer vision and UAV inspection are operationally useful for documentation and access, but automated defect measurement still requires quality control. Distributed fibre optics, acoustic emission, energy harvesting, self-supervised learning, graph neural networks, and fully integrated digital twins are promising but less uniformly validated across long-term field conditions.

A recurring weakness is the use of algorithm-centred performance measures without decision-centred evaluation. Accuracy, F1 score, or reconstruction error does not reveal whether the system detects a maintenance-relevant change early enough, at acceptable false-alarm cost, and with an understandable confidence level. Q1-level future studies should report sensor reliability, missing data, seasonal performance, false positives, false negatives, external validation, computation and communication cost, and the consequences of incorrect decisions.

13. Future Framework

The most important research gap is not the absence of another damage-classification algorithm; it is the absence of long-term, open, well-documented field datasets that contain confirmed deterioration, maintenance interventions, sensor faults, environmental conditions, and independent inspection evidence. Without such datasets, models are evaluated on synthetic damage, laboratory structures, or random train-test splits that do not represent deployment. Benchmark initiatives should include bridge geometry and material metadata, sensor calibration, maintenance events, uncertainty, and clear usage licences.

- Long-term multimodal field validation should combine global response, local NDT, environmental data, inspection records, and maintenance outcomes.
- Physics-informed and hybrid models should report the sensitivity of conclusions to uncertain boundary conditions, material properties, and model form.
- Self-supervised, transfer, and federated learning should be developed for bridge populations while preserving data ownership and avoiding negative transfer.
- Explainable AI should link alarms to physical evidence, uncertainty, and recommended verification, not only provide visual feature attribution.
- Sensor durability, calibration drift, missing data, communication failure, and cybersecurity should be treated as core SHM performance variables.
- Masonry, timber, short-span, rural, and foundation-scour monitoring require greater attention because the literature is concentrated on concrete, steel, and landmark bridges.
- Cost-benefit analysis should compare SHM with inspection, rehabilitation, load restriction, and replacement across the asset lifecycle.
- International data and interoperability standards are needed for sensor metadata, bridge information models, alarms, model versions, and maintenance records.

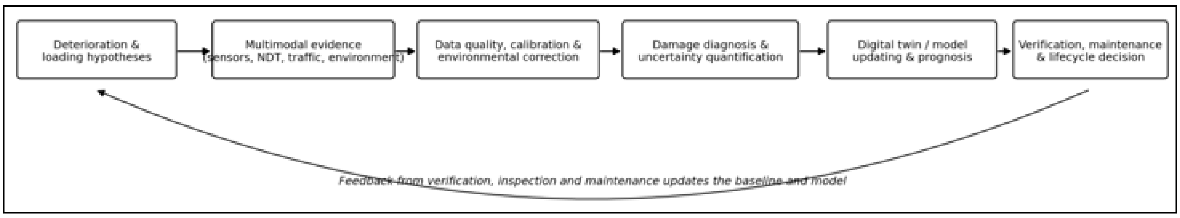

Figure 5: Proposed deterioration-to-decision framework for structural health monitoring of aging bridges.

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Figure 5 presents a future framework in which monitoring begins with deterioration and loading hypotheses, not with data collection alone. Multimodal data are corrected for environmental and sensor effects before damage diagnosis. A digital twin then combines observations with physics-based models and uncertainty to estimate condition and remaining life. Risk-based maintenance closes the loop by recording inspections, interventions, and outcomes, thereby improving the baseline for subsequent decisions.

13.1 Limitations of the Review

The review is limited by inconsistent terminology, heterogeneous damage scenarios, unequal reporting of bridge age and condition, and the absence of common accuracy and uncertainty metrics. English-language and publication-access restrictions may also introduce selection bias. Direct comparison is particularly difficult when laboratory studies use artificial damage while field studies observe uncertain deterioration under changing traffic and environmental conditions. In addition, the supplied source material did not include original database exports or a complete exclusion log; consequently, the PRISMA flow retains editable identification and exclusion counts that must be completed from the final archived search before journal submission. This transparent limitation is preferable to reporting reconstructed or unverifiable screening numbers.

Conclusions

Structural health monitoring can substantially improve the management of aging bridges when it is designed around deterioration mechanisms and decision needs. The review shows that local NDE methods remain the most direct tools for identifying corrosion, delamination, fatigue cracking, voids, and other specific defects. Global vibration, strain, displacement, and environmental monitoring provide continuous evidence of structural behaviour, but their diagnostic value is limited by non-unique response changes and operational variability. Computer vision and UAVs improve access, repeatability, and spatial documentation, while bridge weigh-in-motion and mobile sensing create opportunities for lower-cost network-level screening. No individual method can reliably perform detection, localisation, classification, severity assessment, and prognosis for every bridge type. Hybrid monitoring is therefore the most defensible strategy. Global measurements should identify unusual behaviour; local testing should verify the damage mechanism; calibrated structural models should evaluate consequences; and probabilistic deterioration models should support remaining-life and maintenance decisions. Environmental compensation and sensor-quality management are not preprocessing details but fundamental components of damage diagnosis.

AI and digital twins are changing the scale and automation of bridge monitoring, yet their practical value depends on trustworthy data and validated integration. Scarce damaged-state data, domain shift, limited explainability, model uncertainty, sensor drift, interoperability, cybersecurity, and the lack of maintenance-linked field evidence remain significant barriers. The maturity of a system should be judged by false-alarm control, long-term reliability, uncertainty communication, lifecycle cost, and demonstrated influence on engineering decisions rather than by algorithmic accuracy alone. Future Q1-level research should prioritise open multimodal benchmarks, long-term operational validation, physics-informed and transferable learning, explainable decision support, low-power robust sensing, material-specific monitoring for masonry and timber bridges, climate-aware deterioration prognosis, and standardised digital-twin interfaces. The principal contribution of this review is an integrated deterioration-to-decision perspective: bridge SHM should evolve from isolated sensing and anomaly detection toward a closed lifecycle process that links measured evidence to verified damage, structural consequence, remaining service life, and risk-based maintenance. In direct response to the research questions, corrosion, cracking, fatigue, prestress deterioration, bearing restraint, and scour are the dominant monitoring targets; local NDT and strain/acoustic methods are most effective for specific defects, while global vibration and displacement methods are strongest for behaviour screening. Environmental and operational normalisation remains essential, and the most credible evidence comes from field or full-scale validation supported by independent inspection. AI, UAV, IoT, and digital-twin methods are expanding automation and integration, but implementation is constrained by data scarcity, transferability, calibration, interoperability, cybersecurity, and uncertain lifecycle value. SHM therefore contributes most when hybrid evidence is explicitly connected to verification, structural consequence, remaining life, and maintenance action.

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